INFLUENCE OF STORE CHARACTERISTICS ON PRODUCT AVAILABILITY IN RETAIL BUSINESS

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Introduction

Retail stock-out refers to a situation where a demanded product is not available to the customer in the expected location or is not in a saleable condition (ECR Europe, 2003). Many studies conducted in the last fifty years have shown that the average stock-out rate (percentage of the unavailable products at the time of the audit or purchase) is generally constant and varies between 7% and 8% (Aastrup & Kotzab, 2010). Although extensively studied for decades (e.g. Corsten & Gruen, 2003; Fernie & Grant, 2008; Zinn & Liu, 2001), the phenomenon of stock-outs remains one of the major problems for retailers and manufacturers (Aastrup & Kotzab, 2010).

Corsten and Gruen (2007) found that sales loss due to stock-outs can be as high as 4% of annual sale for retailers and 2.3% for manufacturers. Beside direct losses, stock-outs can cause significant indirect loss in terms of lower customer service and loyalty. Since product availability represents one of the key components of customer service (Gruen et al., 2002; Aastrup & Kotzab, 2009), most authors believe that the solution to the stock-out problem represents a great opportunity for retailers and manufactures to increase their sales and revenue.

In the past few decades, academics have approached the stock-outs problem from several perspectives, including the identification and measurement of stock-outs, identification of drivers of stock-outs and the examination of customers' reactions when they face stock-outs (e.g. Corsten & Gruen, 2003; Fernie & Grant, 2008; Zinn & Liu, 2001). This research contributes to the least investigated aspect of retail stock-outs—the influence of systemic drivers of inventory shortage in terms of store-related contingency factors.

In spite of the fact that some insights about stock-out drivers can be found in the existing literature, these are usually based on a limited number of stores, small number of SKUs (stock-keeping units) or a limited time period. The aim of this research is to overcome some of these limitations by using a larger dataset and different method of stock-out identification. Measurement of the influence of store-related drivers should enable comparison of the results with prior studies and will have enhanced managerial implications.

The rest of this paper has the following structure. A literature review is presented in the second part, which provides an overview of the most significant results regarding drivers of product availability. The research methodology is presented in the third section, which describes sources of data, justification of the selected stock-out identification method and statistical approach. The results and brief discussion are given in the fourth section. Finally, this paper concludes with some managerial recommendations with the goal to improve effectiveness of the overall retail chain.

1. Literature Review

A number of researchers have tried to reveal the drivers of retail stock-outs and the factors that contribute to lower product availability (Corsten & Gruen, 2003; Ronald Berger, 2003; Angerer, 2005; Usman, 2008; Ehrenthal & Stölzle, 2013; Avlijas et al., 2015). Most of the studies that have investigated the causes of retail stock-outs have found that there are major problems in the ordering and forecasting at store level. Store managers are faced with constant promotions and fluctuating demand for thousands of products and they must cope with additional issues, such as reduced storage space and increased product proliferation.

Although the stock-outs can occur anywhere in the entire supply chain, Aastrup and Kotzab (2009) found that 98 percent of

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stock-outs occur at the store level. Similarly, Hofer (2009) found that 91.8 percent, and McKinnon et al. (2007) that 65 percent of all stock-outs are caused at the store. In their global study, Corsten and Gruen (2003) found that about 75 percent of the causes of stock-outs originate from the store operations, while 25-30 percent originates from the distribution centre (DC) or the headquarters operations. Almost half of these causes are associated with the ordering process (i.e. insufficient quantity or late order), which is mostly a consequence of unreliable demand predictions.

Most of the drivers examined in the literature are associated with failures at the planning or execution stages of retail operations. Moussaoui et al. (2016) described operational, behavioural, managerial, and coordination drivers as ‘endogenous in nature’ because they can be directly acted upon to mitigate the risk of stock-outs. The rest of the drivers they described as ‘idiosyncratic in nature’ because they include contingency factors which are difficult to address without changing the overall business strategy. Since retailers have to adapt to these constrains, Moussaoui et al. (2016) categorised these drivers as ‘systemic’.

Ehrenthal and Stölzle (2013) investigated stock-out drivers at the store level and found that the causes of stock-outs are retailer, store, category and stock-keeping unit (SKU) specific. A larger number of studies have examined SKU-related systemic drivers, such as promotional effect (Ettouzani et al., 2012; Avlijas et al., 2015), sales speed (Gruen et al., 2002; Stölzle & Placzek 2004), product price (DeHoratius & Raman, 2008; Van Donselaar et al., 2010), demand variation (Mattsson, 2010), shelf life and case pack size (Andersen Consulting, 1996; Angerer, 2005), availability at the DC distribution (Usman, 2008; Avlijas et al., 2015), inventory level (Angerer, 2005; Grubor et al., 2016), while few studies exist on store characteristics as drivers of retail stock-out performance.

Angerer (2005) used linear regression to examine the impact of store characteristics and ordering automation on stock-out performance. He used a manual audit method to identify stock-outs and concluded that stock-out performance differs from store to store and that more experienced store managers have fewer stock-outs and stores with larger backrooms encounter more stock-outs. He partially proved that a larger number of SKU per square meter increases stock-out rate, too many and too few staff increases stock-out rate, and inventory performance differs from store to store.

Unsman (2008) used point of-sale (POS) identification method and applied data mining techniques to examine the interaction of stock-out performance and other variables, such as store attributes, demographic data and various aspects of inventory management data. The variables that were determined to be the drivers of stock-out performance include distance from distribution centre, average inventory-on-hand, day of week when store was supplied, years the store has been in operation, income level of the area and demographic profile. Grubor and Milicevic (2015) also used POS identification method to analyse the impact of store size on stock-outs and concluded that the average stock-out rate declines with the size of retail formats.

However, some authors have provided different conclusions regarding store size. Aastrup and Kotzab (2009) examined eight larger and nine smaller retail stores, and recorded higher stock-out rates in smaller retail stores. Similarly, a field study conducted by Fernie and Grant (2008) also found smaller stores to be more prone to stock-outs. The results of several other studies (Gruen et al. 2002; Stolzle & Placzek, 2004; Roland Berger, 2003; Aastrup & Kotzab, 2009) have shown that the product availability differs between retail stores within the same format, which was attributed to their size, assortment and number of employees.

In most of these studies, identification of stock-outs was performed using the POS estimation method or manual audit method, so the results and conclusions were mostly based on a small number stores and SKUs, and they were observed in a shorter period of time. The POS method implies the use of mathematical models which estimates stock-outs based on sales trends and it is applicable to fast-sale items only. On the other hand, the manual audit method requires significant time and resource commitment. To overcome these issues and investigate the impact of store related drivers on larger data set, we decided to use the perpetual inventory (PI) aggregation method, which is based on the use of store-level compiled inventory records.

2. Research Methodology

2.1 Data Sample

The data sample was provided by a Serbian grocery retailer that currently operates more than 130 retail stores and has one distribution centre in Belgrade. Most of stores are located within city of Belgrade, which has a population of 1.23 million (over 1.68 million people live within city administrative limits). Information on the sales and inventory was extracted from the retailer's central information system and compiled into a high granulation dataset. To add demographic data, an average salary report was obtained from the Statistical Office of the Republic of Serbia (SORS, 2016). Complete data acquisition, preprocessing and statistical analysis were performed using the statistical software Stata 12.

Data preprocessing and sampling was done in three phases: the first phase included SKU selection, the second phase included store selection and the final phase included data integration. From the assortment of over 10,000 SKUs, two product categories consisting of a total 115 SKUs were extracted for the baby diapers category (comprising 69 SKUs) and toilet paper category (comprising 46 SKUs). These two categories were selected due to the negative effect they produce for retailers, and their suppliers and manufacturers. These negative effects are reflected in the way that the customers react when they face stock-outs in one of these categories.

Corsten and Gruen (2003) state that 40 percent of baby diaper customers worldwide, due to their great product-customer loyalty, change stores in case of a stock-out (i.e. retailer lost sale). On the other hand, a stock-out in the paper towels and toilet tissue category does not mean much for the retailer but it carries the highest risk for the manufacturer or supplier. Corsten and Gruen (2003) found that 37 percent of consumers change brands in the case of a paper towels and toilet tissue stock-out (i.e. manufacturer lost sale). The inclusion of categories with different stock-out effects and price/promotion elasticity reduced the possibility of higher interference of SKU related drivers and their impact on the results.

The next phase of preprocessing included the selection of retail stores. To ensure data reliability, only the stores that recorded complete data were included in the dataset. Stores that had not been operating for a whole period (opened late or closed during that time) or stores with incomplete data due to technical issues were excluded. The final sample included 98 stores with consistent sales during the one calendar year. Since 2012 was a leap year, data sample included 366 days in total.

The last phase of preprocessing included the integration of electronic data obtained from the retailer's Enterprise Resource Planning (ERP) system and average salary data from the Statistical Office of the Republic of Serbia (SORS, 2016). Retail module within ERP is functionally comprised of subsystem for monitoring of all business processes within an individual store, Point of sale (POS – register) subsystem, subsystem for centralized management of retail, data synchronization subsystem, and marketing subsystem. Data obtained from the ERP system included daily sales and inventory reports at a daily level and different kinds of store-related information (store area, distance from DC, store assortment). Primary store data was used to derive new information, such as SKU density, average inventory and average sales. The final dataset included a single high granulation dataset that consisted of 2,953,027 observations at the SKU/store/day level.

2.2 Identification of Stock-Outs

As noted before, one of the biggest problems related to the stock-out data analysis is the method of stock-out identification and measurement. Gruen and Corsten (2007) defined three different methods of stock-out identification: manual audit method (MA), POS estimation and PI aggregation. MA method includes periodic physical checks of the shelves in selected categories, which can be time and resource consuming. POS estimation requires the use of mathematical models and estimates stock-outs based on sales trends, and it is often applicable to fast-sale items only. Finally, PI method is purely based on inventory data and use of store-level compiled inventory records.

To investigate the impact of different store related drivers using a dataset that includes larger number of stores and SKUs, the PI method was chosen for this study. The use of the PI method implies that the quantity in store corresponds to the inventory data recorded in the system, which is often not the case. DeHoratius and Raman (2008) reported that non-compliance can be as high as 65 percent due to a surplus in the ERP system (phantom inventory) or a surplus in the physical state (hidden inventory).

To cope with this issue, the examined retailer carried out checks of their physical inventory twice a month and adjusted the inventory data recorded in the system. To improve the accuracy of the dataset, preprocessing also included cross-checking of inventory data with delivery and sales data at the SKU/store/day level. The PI identification method enables stock-out analysis at store, SKU, or entire level, and provides useful insights over a long time period. One of disadvantages of PI method is that it takes product availability in the store into account, rather than availability of the product on the shelf (as is case with the manual method). Since SKU can exist in the backroom storage but not on the shelf, it can be stated that the actual shelf stock-out performance may be worse than calculated by the PI method.

2.3 Statistical Approach

To model the stock-out performance, a probit regression was selected. A probit model can be used when the dependent variable is dichotomous (binary) and can be described by at least one independent (predictor) variable. When SKU is not available in a certain store on a certain day, the dependent variable takes a value of 1. In contrast, when there is at least one unit in stock, the value of the dependent variable is 0. Therefore, the dependent variable of retail stock-out can be modelled as:

$$stockout_{ijk} = f(store\ variables) \qquad (1)$$

where *i* represents selected store or number of stores, *j* represents selected SKU or number of different SKUs and *k* represents the time period in days. We used probit regression to model all of the 115 SKUs in 98 stores during one whole calendar year (366 days). The independent store variables were: distance from distribution centre, store area, number of SKUs per store, SKU density, total sales, average inventory on hand, and average income in the store area. Several similar approaches were considered to find the appropriate statistical method.

Some of the alternative approaches were rejected due to certain deficiencies, such as ordinary least square (OLS) regression. Although an OLS regression can be used with dichotomous dependent variable, it can yield false results (Long, 1997). On the other hand, some approaches provided similar results (such as logistic regression), so we measured the relative quality of both models using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). These two criterions measure model fit (negatively as *-2 ln(likelihood)* and complexity (positively as *2k* or *ln(N)k)*. The values of these criterions for both models are presented in Tab. 1 and both show a better fit for the probit model, which was selected for this study.

Tab. 1: Model selection statistics

Model	Obs	AIC	BIC
Logit	2,953,027	725,402.7	725,467.2
Probit	2,953,027	725,338.2	725,402.6

Source: own

3. Results and Discussion

Before the main analysis, descriptive statistics and correlation analysis of the variables were conducted. The results of the descriptive statistics of the selected variables are shown in Tab. 2. Descriptive statistics provide insight into the structure of the data and stock-out rate of the selected sample. Form Tab. 2 it can be seen that the average stock-out rate for the selected sample is 2.68. The stock-out rate represents the ratio of the number of observations for which dependent variable stock-out equals 1 and the total number of observations, which represents maximum possible SKU availability.

All of the independent variables were analysed as continuous variables, while the dependent variable (stock-out) was analysed as binary. Given that significantly dependent variables reduce the accuracy of the model and lead to misconceptions regarding the influence of the independent variables, correlation analysis was conducted. Seven different variables were measured and four were included in the final model (i.e. distance from distribution centre, SKU per store density, average store sales, and average income in the store area). Three variables with significant dependence were excluded from the model (i.e. store area, number of SKUs per store, and average inventory-on-hand).

Distance from distribution centre variable (dc_distn) represents how far each store is located from the single distribution centre located in Belgrade, and varies between 5 and 340 kilometres. Since most of stores are located within the Belgrade area, the mean value is 63 km. Store area variable (str_area) represents total area denoted in square meters, including backroom storage. However, information about the backroom storage area was not available and, therefore, this variable could not be included in the model.

Number of SKUs variable (sku_nmbr) represents total number of different SKUs in each store assortment, which varies from 4,202 to 10,128, mostly depending on the available store area. The SKU density variable (sku_dens) represents a number of different SKUs per one square meter at each of the observed stores; that is, a ratio of numbers of SKUs per store and variables store area. Consequently, the variables store area and numbers of SKUs per store had a high correlation with the SKU density (0.84 and -0.58) and, therefore, the variables store area and number of SKUs per store were not included in the model.

Average sales variable (avg_sales) represents average daily store sale, as denoted in euros. Average inventory-on-hand (avg_inven) represents the average number of SKUs on-hand in the store and varies from 25 to 61 units. Since variable average sales had a high correlation with the variable average inventory-on-hand (0.75), variable average inventory-on-hand was not included in the model. Average income variable (avg_incm) represents average salary of population living in the area where the store is located, and varies between 222 and 465 euros.

Tab. 3 shows the probit model for selected variables. *Prob > chi2* represents the probability of obtaining the chi-square statistic when there is no effect of the combination of independent variables on the dependent variable. In other words, this is the p-value, which is compared with a critical value (0.01) to determine whether the overall model is statistically significant. As depicted in Tab. 3, the model is statistically significant and this also true for all coefficients ($P > z$).

Marginal effects were used to interpret the obtained coefficients and measure the impact of independent variables on the outcome variable. The margin represents average predicted probability of a stock-out, which is calculated over a dataset in which some or all of the variables are fixed at values that are different from the actual ones. Another way to calculate the predicted probabilities would be to evaluate margins at the means of covariates, which in our case provided similar results.

Tab. 2: Descriptive statistics of the store variables

Variable	Obs	Mean	Std. Dev.	Min	Max
dc_distn	2,953,027	63.19597	82.49583	5	340
str_area	2,953,027	176.60200	44.34191	59	280
sku_nmbr	2,953,027	8,637.38300	974.44280	4,202	10,128
sku_dens	2,953,027	0.0208823	0.0065666	0.006	0.045
avg_sales	2,953,027	1,863.23000	812.44580	605.1175	4,228.456
avg_incm	2,953,027	332.29150	70.54700	222.9	465.47
avg_inven	2,953,027	34.96184	7.027901	25.5967	61.68919
stock_out	2,953,027	0.0268342	0.1615986	0	1

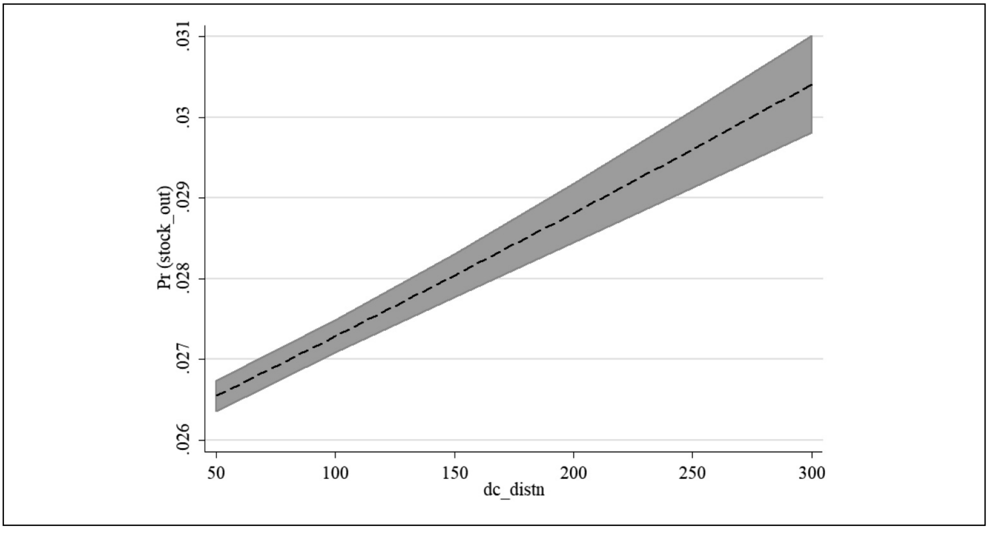
Source: own

Tab. 3: Probit model for the store variables

Number of obs = 2,953,027		Log likelihood = -362,664.08		Pseudo R2 = 0.0061		
LR chi2(4) = 4,417.9		Prob > chi2 = 0.000				
Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**Lower Bound 95% conf. int.**	**Upper Bound 95% conf. int.**
dc_distn	0.00023820	0.00001830	13.04	0.000	0.0002024	0.000274
sku_dens	11.47547000	0.23255860	49.34	0.000	11.01967	11.93128
avg_sales	0.00005500	0.00000186	29.63	0.000	5.14E-05	5.87E-05
avg_incm	0.00007130	0.00002170	3.28	0.001	0.0000287	0.0001138
_cons	-2.32027600	0.00968330	-239.62	0.000	-2.339255	-2.301298

Source: own

Fig. 1: Marginal effects for variable distance from DC

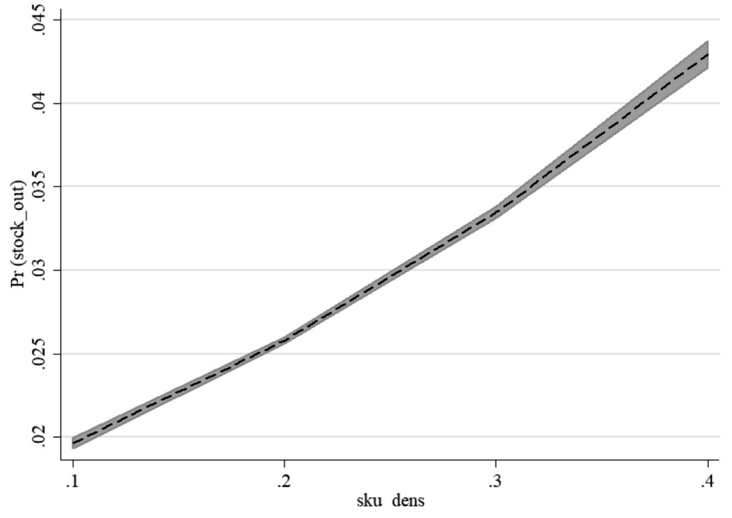


Source: own

The average predicted probability of a stock-out with 95% confidence interval for the continuous variable distance from DC (dc_distn) is given in Fig. 1. The average probability of a stock-out for distance from DC = 50 km was 0.0265 and increased to 0.030 for distance form DC = 300 km. In relation to the store distance from DC, we can conclude that the distance contributes to the increase of the stock-out probability, but it does not have a significant impact on the stock-out performance. Next, the impact of the SKU density on product availability was examined (Fig. 2).

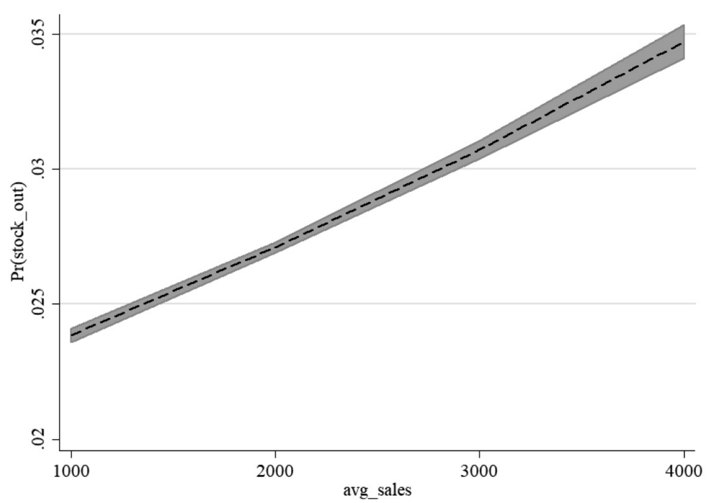
The average probability of a stock-out for SKU density per store = 0.1 was 0.020 and increased to 0.042 for SKU density per store = 0.4. Since the probability of a stock-out doubles with an increase of SKU density from minimum to maximum value, we can conclude that the variable SKU density per store has a significant impact on the probability of a stock-out. Another variable that has a significant impact on stock-

Fig. 2: Marginal effects for variable SKU density per store



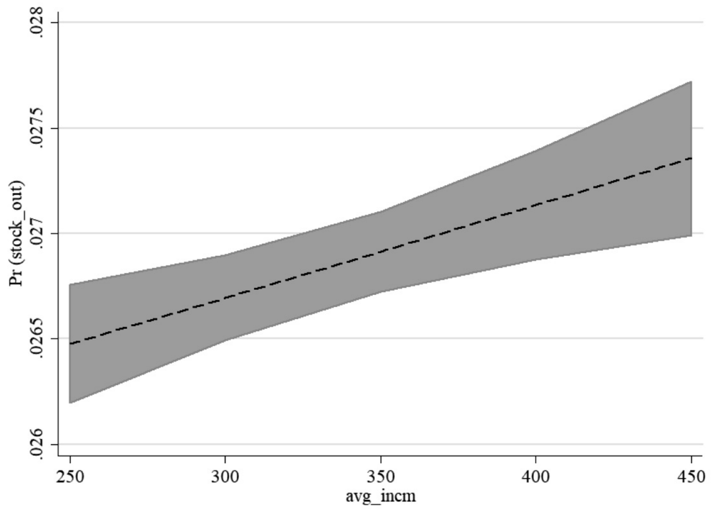
Source: own

Fig. 3: Marginal effects for variable average sales per store



Source: own

Fig. 4: Marginal effects for variable average income



Source: own

outs at the store level is average store sales, which increases the predicted probability of a stock-out from 0.024 to 0.035 (Fig. 3). In other words, the probability of stock-out is about 50 percent higher when store encounters high sales.

On the other hand, this is not true for the variable average income in the store area (Fig. 4). The average probability of a stock-out in the case of store located in highest income area would be 0.027, compared with the opposite situation (store located in the area of the lowest income), and almost the same predicted probability of 0.026. We can, therefore, conclude that the average income of the people living in the store area does not have a significant impact on the stock-out performance.

To examine the marginal effects of the interaction of store variables on the stock-out effect, we discretised the continuous variables into three-interval ordinal variables. In respect to the nature of the variables, rather than any other well-known mathematical techniques of discretisation (such as equal-width and equal frequency binning), we used the following approach: variable distance from DC was discretised so that 1 represents stores located less than 50 km from DC (stores within city area), 2 represents stores located from 50-150 km from DC (stores within wider county area), and 3 represents stores located more than 150 km from DC.

The variable SKU density was discretised so that 1 represents stores with SKU density less than 0.02, 2 represents stores with SKU density from 0.02-0.03, and 3 represents stores with SKU density more than 0.03. The variable average daily sales was discretised so that 1 represents stores with average daily sales less than 1,000 euros, 2 represents stores with average daily sales from 1,000-2,000 euros, and 3 represents stores with average sales of more than 2,000 euros. Variable average income of people living in the store area was discretised so that 1 represents stores located in lower average income area (less than 300 euros), 2 represents stores located in the average income area 300-400 euros, and 3 represents stores located in higher income area (more than 400 euros).

Tab. 4 shows five highest and five lowest marginal effects of the interaction of store

Tab. 4: Marginal effects of the interaction of variables

dc_distn#sku_dens# avg_sales#avg_incm	Margin	Std. Err.	z	P > z	Lower Bound 95% conf. int.	Upper Bound 95% conf. int.
3 3 3 2	0.0470166	0.0007178	65.50	0.000	0.0456097	0.0484236
3 3 3 3	0.0459765	0.0007835	58.68	0.000	0.0444409	0.0475122
2 3 3 2	0.0451330	0.0007431	60.73	0.000	0.0436765	0.0465895
2 3 3 3	0.0441266	0.0007639	57.77	0.000	0.0426294	0.0456238
3 3 3 1	0.0436168	0.0006918	63.05	0.000	0.0422608	0.0449727
…	…	…	…	…	…	…
3 1 1 1	0.0197691	0.0003579	55.23	0.000	0.0190676	0.0204707
2 1 1 1	0.0188528	0.0003241	58.17	0.000	0.0182176	0.0194880
1 1 1 2	0.0184875	0.0002530	73.06	0.000	0.0179915	0.0189834
1 1 1 3	0.0180088	0.0002637	68.31	0.000	0.0174920	0.0185255
1 1 1 1	0.0169306	0.0002428	69.73	0.000	0.0164547	0.0174065

Source: own

variables on stock-outs. The first line reports the marginal probability of a stock-out in situation when dc_dist=3, sku_dens=3, avg_sales=3 and avg_incm=2. Namely, it represents the estimated probability if every observation in the data was treated as if the store was located more than 300 km in the average income area, with SKU density more than 0.03 and average daily sales of more than 2,000 euros, which is the worst-case scenario. Obviously, the best-case scenario is 1-1-1-1, with the predicted stock-out probability of 0.016 (i.e. store was located close to DC, in the lower income city area, with SKU density less than 0.02 and average daily sales less than 1,000 euros).

Although the analysis confirmed some effect of all four examined variables on retail stock-outs, impacts of SKU density and average store sales variables were considered as significant. These results confirmed findings of Angerer (2005) that larger number of SKU per square meter increases stock-out rate, but denied some findings of Unsman who found that distance from distribution centre and income of population living in the store area have impact on stock-out performance. Different conclusion can be attributed to insufficiently heterogeneous sample when it comes these two variables. Since most of the retail stores were located near to the capital city, variation of distance from the distribution centre and average income of population living in the store area might not have been large enough to express significant impact.

Conclusion

Regardless of the practical and scientific effort, stock-outs still remain one of the least determined, measured and explored performance measures of the entire supply chain. This paper contributed to the scarce academic knowledge on drivers of stock-outs at retail store level and investigated some of the literature-based threats in terms of the store characteristics. Analysis showed that the number of stock-outs per store depends on number of different SKUs per square meter. So-called SKU density per square meter proved to be the most prominent driver of stock-out performance because the probability of stock-out doubles with higher levels of SKU density. This added a new value to some of the prior results and shed some light on the less explored store space-related variable.

Beside high item density, probit regression revealed another significant driver, as reflected in higher store sales. Higher sales consequently contribute to higher inventory turnover and demand variation, which are already proven to be high-risk SKU-related drivers of retail stock-outs. Therefore, store managers should pay more attention to the stores with wider assortment and higher sales, and especially when it comes to a combination of these two. The results of the interaction of variables analysis confirmed that the highest probability of stock-out can be expected when SKU density and average store sales are high.

Although the analysis confirmed that an increase in the distance from DC and income of population living in the store area led to the increase stock-out probability at the retail store level, we can conclude that there is not enough evidence to treat this increase as significant. It is important to state that distance of stores from DC and general income range may have not been wide enough to express the full-scale effect on retail stock-outs, as was the case with some of the prior results found in the literature.

Research confirmed that certain characteristics of retail stores can lead to a higher rate of stock-outs in retail business. Since data set included grocery type products, research findings are mainly related to fast selling and cheaper consumer goods. Perpetual inventory (PI) aggregation method of stock-out identification has proven to be efficient on a large data set, but one of the limitations of such approach is that it takes product availability in the store into account, rather than availability on the shelf. In order to confirm obtained results and expand insights, further analysis could include manual audit method of (shelf) stock-out identification, larger number of examined product categories, and inclusion of product related variables.

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Abstract

INFLUENCE OF STORE CHARACTERISTICS ON PRODUCT AVAILABILITY IN RETAIL BUSINESS

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Stock-out event in retail business represents a situation in which demanded item cannot be found by customer in the expected location or is not in a saleable condition. Frequent stock-outs remain one of the biggest issues in the retail business because they directly contribute to lost sales and reduced profits, and indirectly contribute to reduced loyalty and potential loss of customers. Although the stock-outs can occur anywhere in the entire supply chain, literature confirmed that the most of most of stock-outs occur at the store level. A number of researchers have tried to reveal the product and store related drivers and the factors that contribute to lower product availability. Identification of stock-outs was usually performed using the point-of-sale (POS) estimation method or manual audit method, so the results and conclusions were mostly based on a small number stores and products, and they were observed in a shorter period of time. In this research, probit regression was used to examine the relationship between various store-related drivers and product availability. The data sample included 115 SKUs and 98 stores and the data was provided by a large grocery retailer in Serbia. To identify stock-outs on a large data sample, a perpetual inventory (PI) aggregation method was selected. The store related variables that were determined to be the drivers of stock-out performance include distance from distribution center, average store sale and stock-keeping-unit density as the most the most prominent driver. Especially high probability of stock-out can be expected when stock-keeping-unit density and average store sale are high at the same time. On the other hand, it was observed that the income level of the population living in the store area does not have a significant influence on stock-out performance at store level.

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